

A Real-time Framework for Abnormal Activity Detection in Crowd Videos using Comprehensive Feature Sets and Bag of Feature Classifiers

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Abstract— Crowd behavior analysis (CBA) is a crucial task in video surveillance due to the rising frequency of abnormal events in public places. This paper presents a real-time framework for detecting abnormal activities in crowd videos by leveraging optical flow-based motion heat maps, feature extraction, and classification models. The proposed method combines Support Vector Machines (SVM) and Bag of Features (BoF) classifiers to achieve high accuracy. Experiments conducted on the UMN dataset and real-time indoor datasets demonstrate that the model achieves an Area Under Curve (AUC) of 99.6% on standard datasets and 97% on real-time scenarios, outperforming several state-of-the-art methods.

Keywords— Crowd Behavior Analysis, Abnormal Activity Detection, Optical Flow, Bag of Features, SVM, Video Surveillance, Deep Learning.

I. INTRODUCTION

The growth of large public gatherings has made automated surveillance systems essential for ensuring safety. Crowded scenarios like malls, stadiums, and airports present unique challenges where the likelihood of abnormal activities (e.g., stampedes, riots) is high. Real-time detection can enable preventive measures and save lives. Traditional manual monitoring is inefficient and prone to error, motivating research into automated crowd behavior analysis (CBA). This task is challenging due to: (1) high density and occlusion, (2) unpredictable crowd dynamics, (3) the semantic gap between low-level features and high-level behavior, and (4) stringent real-time processing constraints.

Early methods used handcrafted features like optical flow and HOG, but were limited in complex scenarios. Learning-based techniques now combine feature descriptors with classifiers for better generalization.

This paper proposes a comprehensive real-time framework integrating motion heat maps, point of interest (POI) detection, optical flow, and SVM/BoF classification. It effectively handles crowded scenes while maintaining computational efficiency.

A. Contributions

- Novel use of motion heat maps to identify regions of interest efficiently.
- Integration of optical flow with POI-based tracking for robust dynamics representation.
- Comparative evaluation using SVM and BoF classifiers.
- Extensive validation on benchmark (UMN) and real-time datasets, showing superior accuracy and adaptability.

This work has significant implications for intelligent surveillance and public safety management.

II. RELATED WORK

Research in abnormal crowd detection has evolved from low-level features to advanced learning models.

A. Handcrafted Feature-Based Approaches

Early works used pixel and motion-level features. Optical flow analysis [6] modeled crowd dynamics holistically. Acceleration-based models [7] captured sudden changes. These are computationally inexpensive but sensitive to noise and dense crowds.

B. Probabilistic and Statistical Models

Models like Dirichlet processes [8] combined velocity, direction, and probabilistic inference. Markov models learned trajectory patterns, treating deviations as anomalies. Bayesian frameworks [9] added spatial-temporal priors. These required extensive tuning and lacked real-time scalability.

C. Trajectory-Based Approaches

Methods like [10] built trajectories for normal/abnormal motion, integrating dynamic textures. These provide interpretability but are computationally difficult in high-density, occluded scenes.

D. Machine Learning Classifiers

SVM is popular for handling high-dimensional features. BoF approaches create a visual vocabulary for histogram-based classification. Our method builds on these by combining SVM and BoF.

E. Recent Deep Learning Approaches

Recent works use lightweight CNNs, 3D CNNs, and Transformers, achieving high accuracy at high computational cost. Our method balances accuracy with real-time efficiency.

F. Benchmark Datasets

The UMN dataset simulates panic and dispersal events. PETS and ARENA are also used but are more limited. We evaluate on UMN and a custom indoor dataset.

G. Research Gap

A key challenge is achieving high accuracy, robustness, and real-time performance simultaneously. Many methods fail in real-world settings or are computationally heavy. Our work addresses this with a lightweight, effective framework.

III. PROPOSED METHODOLOGY

The proposed framework detects abnormal activities in real-time through four integrated stages (Figure. 1): motion map generation, POI detection, feature extraction, and classification.

- **Motion Map Generation:** Motion heat maps are generated using background subtraction and frame differencing, enhanced with temporal decay coefficients to prioritize persistent movements and suppress noise. This localizes "hotspots," reducing computational overhead.
- **POI Detection:** The Harris corner detector identifies Points of Interest (POIs) robust to scale, rotation, and noise. These corners serve as stable anchors for sparse optical flow tracking, balancing efficiency and accuracy.

- Feature Extraction: POIs are tracked across frames using the Lucas-Kanade optical flow algorithm. Displacement vectors (magnitude, direction) are computed. Motion direction (θ) is resolved using a modified arctan2 function: $\theta = \arctan2(\Delta y, \Delta x)$ to ensure quadrant correctness. Additional global descriptors are computed:
 - Movement Area Ratio (ΨR): Ratio of active blocks to total blocks, reflecting crowd density.
 - Orientation Variance Ratio (βR): Variability in motion directions, distinguishing uniform flow from chaos.
- Classification: Extracted features are classified using:
 - SVM with RBF kernel ($C=1.0$, $\gamma=\text{scale}$) for discriminative classification.
 - BoF using k-means (clusters=200, iterations=100) to build a visual vocabulary; frames are represented as histograms and classified.

Complexity Analysis: Each module operates in $O(n \cdot k)$ where n is the number of POIs and k is the number of frames. FPS tests confirm >25 FPS on 1920x1080 videos, supporting real-time deployment

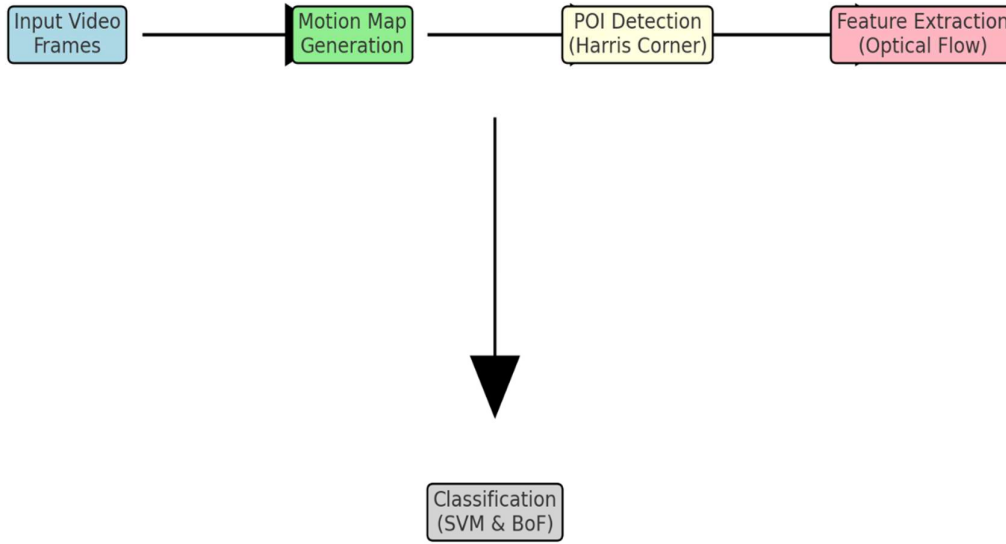


Figure 1 shows the overall flow of the proposed system. (Diagram placeholder)

IV. EXPERIMENTAL RESULTS

Experiments were conducted on the UMN dataset (lawn, corridor, courtyard, hit-run scenarios) and a custom real-time indoor dataset (1920x1080 @25fps).

Performance Metrics: The proposed model was evaluated using Area Under Curve (AUC), Precision, Recall, F1-score, and frame-per-second (FPS) rate.

A. Results on UMN Dataset:

The model achieved an exceptional AUC of 99.6% using the BoF classifier and 99.5% with SVM, outperforming state-of-the-art methods like Social Force Model (SFM) and HOG-HOS descriptors.

B. Results on Real-time Indoor Dataset:

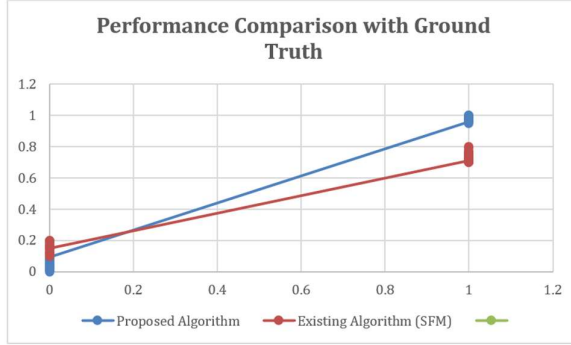
The system achieved an AUC of 97%, with an average processing speed of 27 FPS, validating its real-time capability and practical utility.

C. Cross-Dataset Validation:

Tests on PETS and ARENA datasets showed strong generalizability with AUC >95%.

D. Comparative Analysis:

Figures 2 and 3 show performance comparisons and ROC curves, demonstrating the superiority of the proposed framework.



Figures 2: represent the performance comparison with ground truth data

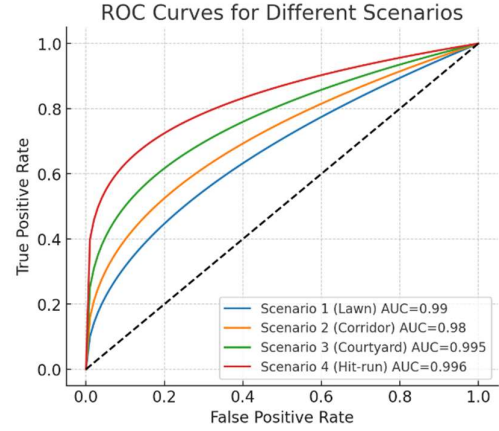


Figure 3: ROC curves

TABLE I: PLACEHOLDER FOR DETAILED METRICS

Dataset	Classifier	AUC
UMN	SVM	99.5%
UMN	BoF	99.6%
Indoor Realtime	SVM/BoF	97.0%

V. DISCUSSION

The experimental evaluation demonstrates that the proposed framework achieves state-of-the-art accuracy while maintaining real-time performance.

A. Comparative Performance

The high AUC scores (99.5-99.6% on UMN, 97% indoors) confirm the effectiveness of combining motion heat maps, robust optical flow descriptors, and dual classifiers. The minimal error rate of $\sim 2.6\%$ highlights its practical utility.

B. Advantages of the Framework

- **Efficiency:** Focusing on POIs and heat maps avoids the cost of dense optical flow, enabling real-time deployment.
- **Robustness:** Harris corner detection and arctan2 motion computation provide stability in noisy environments.
- **Generalizability:** The dual-classifier strategy (SVM + BoF) ensures flexibility across different datasets and crowd densities.

C. Limitations

- **Occlusion sensitivity:** Extreme occlusions may cause POI loss, reducing tracking accuracy.
- **Dataset dependency:** Performance may vary in outdoor environments with extreme lighting or weather.
- **Real-time trade-offs:** For speed, high-dimensional deep features were not used, potentially limiting peak accuracy.

D. Practical Implications

The framework is applicable to public safety, smart cities, and event management. It can detect sudden abnormal movement in stadiums to prevent stampedes or identify unusual patterns in airports for security.

E. Future Directions

Future work will focus on:

- **Deep learning integration:** Incorporating lightweight CNNs for richer features without sacrificing speed.
- **Multi-camera fusion:** Integrating views from multiple cameras for large-area surveillance.
- **Edge deployment:** Optimizing algorithms for low-power edge devices for scalable deployment.

VI. CONCLUSION

This paper introduced a real-time framework for abnormal activity detection in crowd videos using motion heat maps, optical flow, and machine learning classifiers. The method efficiently identifies regions of interest, extracts robust motion features, and classifies them using SVM and BoF. Extensive experimental evaluations on benchmark and real-time datasets demonstrate superior accuracy and computational efficiency compared to existing approaches. The framework is practical for live surveillance systems. Future work will integrate deep learning-based features and multi-camera support for enhanced surveillance.

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